Detection of Apnea using Short Window FFT Technique and Artificial Neural Network

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ABSTRACT

Sleep apnea is characterized by frequent prolonged interruptions of breathing during sleep. This syndrome causes severe sleep disorders and is often responsible for development of other diseases such as heart problems, high blood pressure and daytime fatigue, etc. After diagnosis, sleep apnea is often successfully treated by applying positive air pressure (CPAP) to the mouth and nose. Although effective, the (CPAP) equipment takes up a lot of space and the connected mask causes a lot of inconvenience for the patients. This raised interest in developing new techniques for treatment of sleep apnea syndrome. Several studies have indicated that electrical stimulation of the hypoglossal nerve and muscle in the tongue may be a useful method for treating patients with severe sleep apnea. In order to be able to successfully prevent the occurrence of apnea it is necessary to have some technique for early and fast on-line detection or prediction of the apnea events. This paper suggests using measurements of respiratory airflow (mouth temperature). The signal processing for this task includes the use of a short window FFT technique and uses an artificial back propagation neural net to model or predict the occurrence of apneas. The results show that early detection of respiratory interruption is possible and that the delay time for this is small.

Key Words: sleep apnea, electrical stimulation, signal processing, respiratory airflow, neural network prediction.

1. INTRODUCTION

Sleep apnea is defined as a respiratory disorder characterised by prolonged interruptions of normal respiration during sleep due to a collapse of the upper airway. The apnea syndrome may cause problems ranging from fatigue and chronic daytime sleepiness to life-threatening conditions. A general introduction to sleep apnea is found in, e.g. [1], while more details are found in [2-6] and the references therein. Patients with sleep apnea syndrome are generally divided into different categories depending on the cause. The category of main interest for treatment with electrical stimulation are those with so called *obstructive sleep apnea*. In this case the apnea condition is caused by collapse of tissues in the upper airway where the characteristic of this condition is an absence of airflow despite breathing efforts. As in *central sleep apnea*, which occurs when the respiratory centres in the brain fail to send the necessary "messages" to initiate breathing, a life threatening lack of oxygen and a build-up of carbon dioxide cause the sleeper to wake.

In many cases a continuous positive airway pressure (CPAP) mask [2] during sleep is the most effective non-invasive therapy for treatment of apnea. Although effective, CPAP is inconvenient and sometimes difficult to use for many patients. Several studies [8-11] have offered the possibility of preventing the occurrence of apnea events by applying electrical stimulation. However, it is more uncertain whether and how electrical stimulation effects the hypopnea condition which is often connected to the obstructive apneas.. The present investigation is a part of a larger project [7] to study the use of implants for electrical stimulation of relevant nerves and muscles. Here we investigate the various possibilities of detecting sleep apnea from the signals of a monitoring system. In an ideal system, a control unit will obtain multi-sensor signals, including feed-back information from the implant. This system should be redundant and with a noise-tolerant manner with a good ability to generalise, for example an artificial neural network. The main task is to perform automatic prediction or detection of apnea events. The use of single as well as fused signals is discussed.

2. ELECTRICAL STIMULATION FOR TREATMENT OF SLEEP APNEA

Electrical stimulation may be considered applied either to nerves or to muscles. In these two cases there are different requirement with respect to the electrodes, the power and the frequency of the signal. Considering nerve stimulation, the HG-nerve is generally chosen for bilateral stimulation using two electrodes. Stimulation of the genioglossus

muscle is applied using a single electrode and a common ground. However, there are reasons to believe that there are many problems associated with both types of electrical stimulation's, the main one being fatigue. In this specific case, the objects of stimulation will be both hypoglossal nerves or the genoglossus muscles entering the body of the tongue. The electrical stimulation at that site may spread and activate part of the tongue muscle.

2.1. Timing of the stimulation

From the technical, or detectability point of view the apnea begins when the breathing stops. Often an apnea is defined when there has been no sound of breath for at least five or ten seconds. Another problem to consider in this case is the presence of hypopneas characterised by a considerable decrease in amplitude of breathing, but no total interruption. A high degree of hypopnea periods will result in a long-term decrease of oxygen saturation of the blood. The stimulation is preferred to be applied as soon as there is a sign of a coming apnea. One of the goals for the task is to be able to predict the occurrence of an apnea as early as possible. If the prediction is successful the stimulation will be applied just before the apnea begins, else the stimulation will be applied as the apnea has been detected and during the apnea.

2.2. Defining and detecting apnea events from the sensor signals

Detection of apnea can easily be performed visually by off-line studying of the signal of respiratory airflow, where apneas may be seen as long periods, (often >10 sec), with no or very small airflow. Automatic detection of apnea events may be performed using many different methods. However, the choice of method is depending whether the detection is planned to run on-line preferring early detection or off-line at some later time. In this specific case there is a preference for early detection of apnea and for this situation, using neural network modeling was proposed as a suitable method considering the need for fast on-line detection. As the available data set did not contain any information on apnea occurrence there was a need for some pre-processing method for automatic classification of the data in order to provide the neutral network with the guidance necessary for training purposes, i.e. "desired output". The classification as well as the network training is considered for off-line processing, while prediction from the trained neural network is considered for on-line processing. The automatic classification of apnea events is made using a technique based on short-window FFT applied on the signal of respiratory airflow. In this case the window is moving one step a time through the data set and consequently mainly overlapping.

The respiration may be measured as the magnitude and direction of airflow through mouth or nose. Thus the measured signal of respiration appears as an oscillation of a certain amplitude and frequency. When a patient is suffering from apnea the respiration is repeatedly interrupted by periods of substantial decrease in the airflow. In order to detect apnea it is important to establish where the interruption appear in the signal. One way of doing this is to transform the respiratory air flow signal to a form that does not show the respiration oscillation and that clearly show the difference between respiration and apnea events. For example one could use some short term mean of signal amplitude. The apnea events are characterized by a substantial decrease in amplitude of the signal. A study of the time series signal show that this is not just a sudden stop or interruption of airflow. The apnea event rather begins with a decreasing amplitude of the oscillation of respiration. As the goal of the study is to predict the appearance of apnea it is important to consider the observed decrease in oscillation amplitude that precedes an apnea event.

2.3. Recording of signals related to apnea

The present study is based on data resulting from standard recordings made during sleep studies of patients with suspected sleep apnea. The measurements have been made simultaneously during one night and the time between each measurement is 0.25 seconds. A sleep study normally concern the measurements of (six or)seven different parameters.

- respiratory air flow
- respiratory sound
- respiratory movement
- pulse
- oxygen saturation
- position
- mattress movements

It is necessary to evaluate which of the measured variables are the best for prediction of apnea events. The most obvious variable for detection of apnea is the respiratory air flow measurements. Obviously there will be no respiratory air

flow when there is no respiration. This variable is normally used to define apnea events manually or automatically. In order to be able to investigate the capabilities of apnea detection or prediction, we need to have information about where apnea events appear in the time series signals.

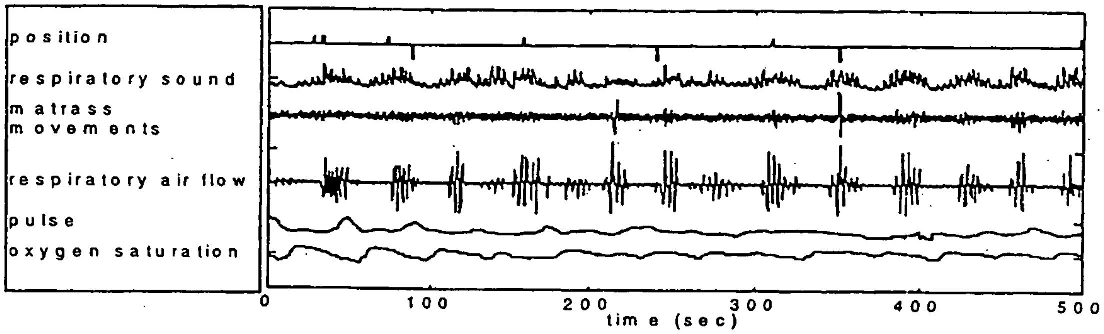


Figure 1. Example of data recordings used for apnea detection

3. DETECTING APNEA EVENTS USING THE SHORT MOVING WINDOW FFT TECHNIQUE

The goal is to detect the beginning and end of apnea events. As mentioned earlier, the features that separates apnea from normal respiration are changes in the instantaneous magnitude, and also in short term mean signal amplitude. Thus a signal showing short window moving average of signal amplitude versus time could indicate the appearance of apnea

3.1. Time dependent short time Fast Fourier Transform (FFT)

One way of estimating the amplitude of a signal is to use FFT calculation. However, FFT-results give no time dependence information about the signal. Normally the condition for application of FFT algorithm is that the signal is continuous and not time dependent. This does not seem to be applicable in this case. What we want to do is to detect time-depending changes in the signal. However, in this case there is normally a certain period of time between changes in the signal. If we use this information we can assume that the signal is continuous or uniform during a certain period of time. The signal is considered uniform in the respiration part and also in the apnea part. Using these conditions we can divide the signal into small "windows" consisting of a certain number of points to use for FFT analysis. If we consider the middle of this window as the time-point of analysis we can then move this window with one point and get one signal array for each point. Thus we can get the amplitude (eg. main frequency amplitude) for each point in the total signal array although calculated using a number of signal points before and after this point. Similar information may also be received using other methods such as a moving average or standard deviation for short periods of the signal.

3.2. Choosing the length of processing window

The essential parameter to construct a proper and useful amplitude signal is to choose a proper length of the signal window used for the FFT. This has been tested with different window lengths applied on the measured signal. The figures 2 a,b show original air flow measurements as well as the resulting curve form for window lengths of 16 points, respectively.

The result from the test presented in figures 2a-b show that the choice of window length is an optimization problem. On one hand, the FFT applied to long time series gives higher differences in amplitude between apnea and respiration. Also the shape of the resulting amplitude curve is smoother and highly continuous within the different conditions (apnea or respiration). On the other hand, the FFT applied to short time series gives sharper slopes of the curve at beginning and ends of apnea events which, in turn, will give better defined apnea regions. However, this does give lower amplitude differences between apnea and respiration and the respiration parts of the curve will have a less smoothed shape and will be more choppy (or "bumpy"). In this specific case, a 16 point window was chosen for FFT processing of the signal.

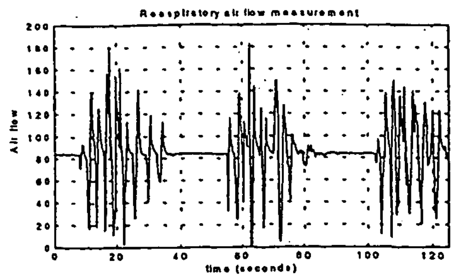


Figure 2a. Air flow measurements showing apnea events

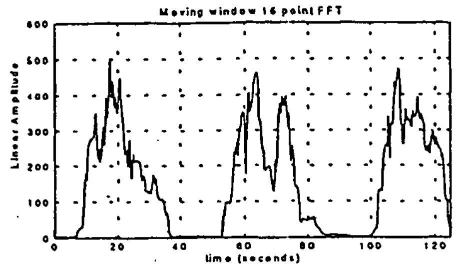


Figure 2b. Results for a 16 point FFT

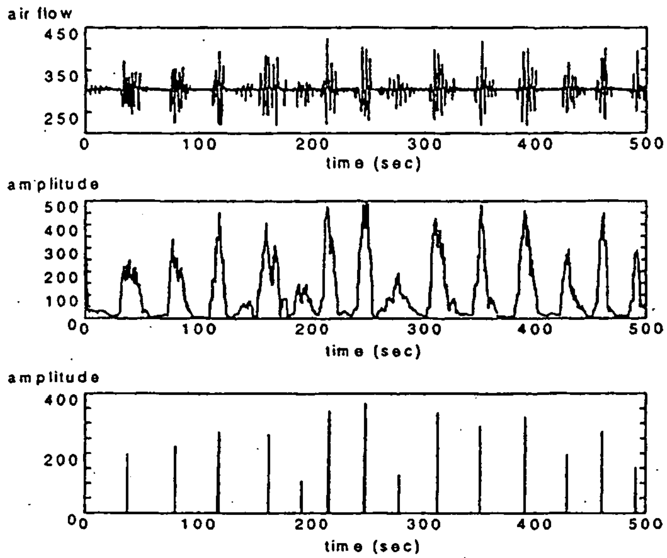


Figure 3. The upper panel shows measurements of respiratory air flow versus time. The middle panel shows linear relative amplitude curve results from 16 point short time moving window FFT of the upper panel data. The lower panel show results from peak detection of peaks in the middle panel

3.3. Conditions for definition of apnea events

When we have received the amplitude signal for the respiratory flow measurements it is necessary to apply a discrimination function. The purpose of this function is to decide where the apneas appear and where they do not. In order to do this we need to have a sharp definition of apnea. We have chosen to say that apnea occurs when the amplitude decreases below 50 % of the previous maximum amplitude of respiration. Another condition for apnea may be that the decrease in amplitude lasts for at least 10 seconds.

The result from a 16 point short time moving window FFT is expressed in terms of maximum amplitude resulting from the FFT calculations (figure 3). In this figure breathing is represented as peaks of high amplitude and apnea events occur as periods of very low amplitude between the peaks. The definition of apnea events is strongly coupled to the definition of breathing. Thus, in order to detect apnea it is necessary to detect the peaks of respiration. With the intention of getting a smoother curve for peak detection the peak is defined as the point on the amplitude curve where the values before and after are lower then at this point. As the system should not produce several peaks for each short respiratory event, only one peak is allowed in an area of 60 points. If there are several peaks in this area, the highest peak is chosen. This may occur as each event of respiration is not smooth and that may be several peaks.

3.4. Detection of apnea events

In terms of the amplitude scale, apnea events are defined as occasions when the amplitude decreases below a certain level compared to the heights of the surrounding peaks. The results from peak detection of figure 3 are used together with results of FFT amplitude (figure 3) to perform automatic detection of apnea. This is made by comparing the values of the signal amplitude to the heights of the surrounding peaks. If the amplitude of the signal at a specific point is below 50 % of the nearest peak then apnea is occurring at this point. An example of results from apnea detection is shown as a square shaped signal in figure 4.

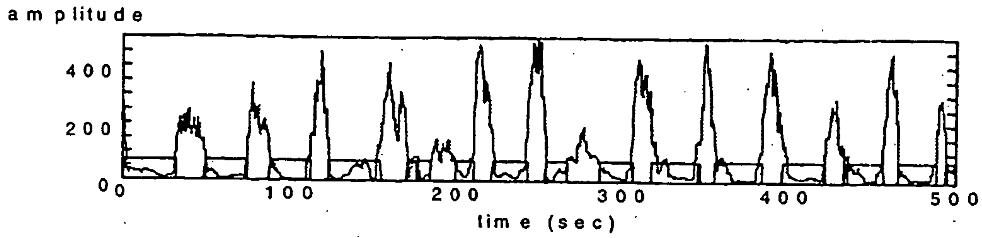


Figure 4. Result of apnea detection together with FFT amplitude of the corresponding signal.

4. TEST OF PREDICTABILITY OF APNEA USING A NEURAL NETWORK

The task of this work is to make fast automatic detection and prediction of apnea events using as few measurers as possible. The purpose of this is to indicate when to activate electrical stimulation of the tongue muscle. The results from apnea classification together with training data was fed to an artificial back propagation neural net to model or predict the occurrence of apneas. Attention has been paid to the pre-processing of these signals and the possibility to use a neural network approach to predict the occurrence of apneas. In this test the neural network was trained using data from one patient. New data from the same patient but also from a second patient were then presented as test data to the same network.

We have chosen a simple feed-forward architecture with one hidden layer and a back-propagation training algorithm. This type of neural network is similar to a transversal filter. However, a non-linear activation function, e.g. a sigmoid function, is used. In this way one can apply the backpropagation learning where the coefficients or weights are obtained by using a training set of data. This method allows fast studying of the possibility of modeling the data and it will also give hints on the contribution of different variables to the resulting prediction. Various numbers of inputs were tested, while the networks always consisted of one hidden layer and one output, furthermore the neural networks were configured using the connect prior function.

In the first approach the neural network had 60 inputs. The inputs to this network was a time series of the last 10 values for each of the 6 measured variables, for a total of 60. The neural network was trained using the back-propagation paradigm. The desired output of the network is a signal of apnea/no apnea state. The network should, we hope, be able to learn to predict apnea events from the input data,. i.e. the coupling between input data and apnea occurrence. The data set used for training of the network consisted of 8000 samples corresponding to approximately 33 minutes of measured data.

The results from this test did not provide a clear prediction of apnea. However, the results from adding a small change in each of the input parameters did show that the largest contributions to modeling the data comes from the values of the pulse measurement represented by variables 41-50 in the data set. The contribution from other variables are small but it is generally highest at points closest to latest time point. Considering the shape of these signals (se figure 1) show that these signals of pulse and oxygen saturation are tendency signals while the other signals are oscillating signals and therefor more difficult to model.

4.1. Neural network modeling (NNM) using pulse and mean value of respiratory flow

As tendency signals are easier to model than oscillating signals it might be to advantage using some method to create tendency signals from the oscillating ones. This might help to in a proper way describe the connection between the input signals and apnea events to the neural network, i.e. make the modeling task easier. A second test trained a back

propagation network using ten point time sequence data of pulse measurements and the mean value of the ten corresponding values of air flow measurement, for a total of 11 inputs. The data set consisted of 10000 values and was divided into a training set of 8000 values and a test set of 2000.

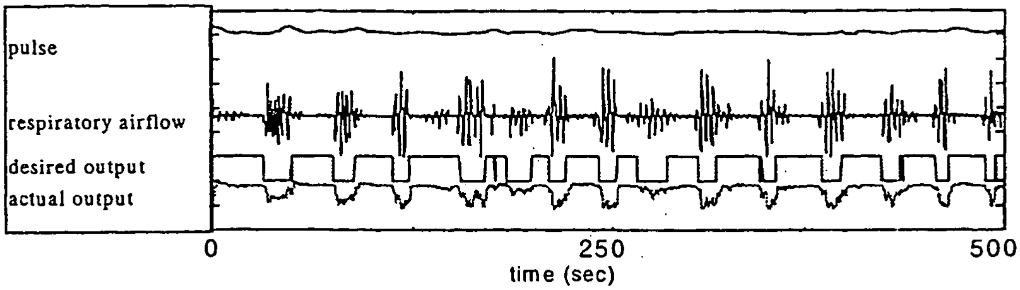


Figure 5. The figure shows training results of the neural network together with desired output (occurrence of apnea) and air flow data and pulse data.

4.2. Result of NNM training using 12 input values of respiratory air flow

In the third case the neural network was using a 12 points input configuration and classification of apnea (0 or 1) as desired output.

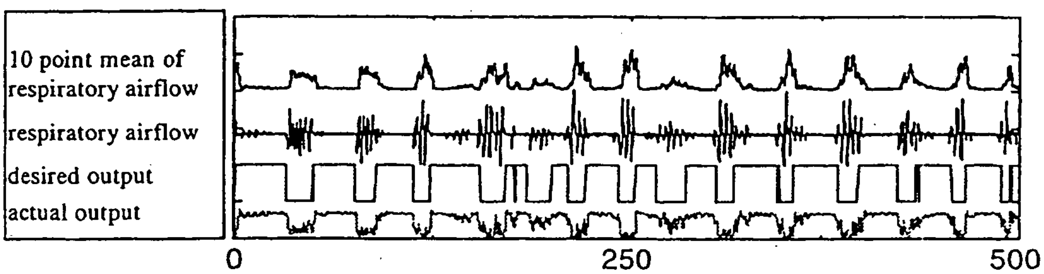


Figure 6. Training results from NN together with desired output (occurrence of apnea) and air flow data and 10 p mean value for air flow.

The results of figure 6 show the output from a neural network that have been trained on 12 inputs constructed from respiratory airflow measurements. The first five values in the training set is 5 sequential values of mean for 10 sequential measurements. The other 6 inputs are differences between the different mean-values of flow. In this result the actual output from the artificial neural network shows good agreement with the desired output of the network corresponding to the occurrence of apnea events.

Figure 7. A comparison of actual output from the neural network to the desired output.

The back propagation neural network algorithm employed here uses a sigmoid activation function for the output weights. This means that even if the desired outputs are just 0 and 1, the actual output has a considerably smaller magnitude. In order to compare the actual output to the desired output, the levels of the desired output values have been adjusted to match the levels of the actual output. Thus the minimum and maximum levels of the desired output have been changed from 0 and 1 to 0.15 and 0.7. The actual output show strong agreement with the desired output. However, it may be seen that the shape of the actual output is rounder than the desired output. See figure 7. This shape is due to the use of windowing

technique where the prediction is based on both earlier and current values of the flow. This means that the contributions of variations in the measurements will be accumulated as from the beginning the change is only visible in a small part of the processing window. After the desired output function has been adjusted, the mean value and standard deviation of the error (difference) between actual and desired output is:

- mean value of error: 0.0080
- standard deviation of error: 0.16

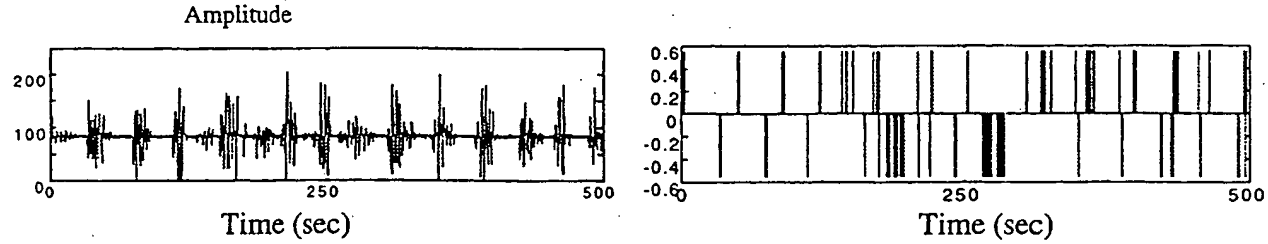


Figure 8. The left panel shows the respiratory air flow as a function of time in sec. The right panel shows the error in the difference between actual output from the network to the desired output.

A study of figure 8 indicate that there seems to be a small time delay for the actual output of the network as compared to the desired output. To study and visualize the time delay, the signals have been shifted at increasing time-steps toward each other (cf. figures. 9 and 10). For each value of the time shift the present error (difference) between the signals have been calculated and corresponding mean values and standard deviations estimated. The figures show that the minimum standard deviation is found for a shift between the desired and actual signals corresponding to 0.5 -0.7 seconds. From figure 10 it may be seen that there is a minimum for the mean error at a time shift of about five seconds. The magnitude of the time delay between actual and desired signals are best described by the minimum of standard deviation.

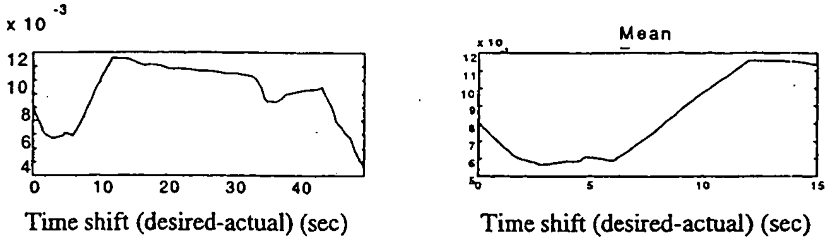


Figure 9. The figure show the mean error in the difference between the actual output from the network and the desired output for different time shifts (in seconds).

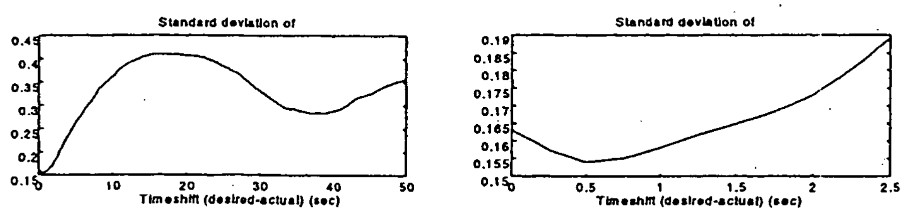


Figure 10. The standard deviation as a function of time for the two cases of figure 9.

4.3. Evaluation of trained neural network using a different set of data

In order to test the ability of generalization and the robustness of the results from the trained neural network the obtained result from a new data set was used in this test. This data was obtained from a different patient. The second data set has been recorded using a slightly different equipment producing some different variables as output. The main difference between the two data sets is different type of sensors for sound recording with different levels of sensitivity. Figure 11 show examples of the measurements of the second data set used for evaluation of the trained neural network. By looking at the

recordings of respiratory airflow it is obvious where there is apnea or not, when there is no airflow there is apnea. Studying the 7 signals of figure 11 show that the signs of apnea are present in all of the signals, except position, however to different extent and with different time of delay.

An input file were constructed in the same way as in section 4.2 but using data from the second data set. The input file were presented as a test file to the earlier trained neural network. (see section 4.2). The result of this test is presented in figure 12. The result from using the second data set as a test set for the neural network trained on the first data set show that the apnea detection is very well performed, although the test signal from the second patient show different signal levels and a slightly different shape. The conclusion from this is that a neural network trained using data from one patient can very well be used for apnea detection on data from an other patent. This result indicates that a neural network based detection/prediction as the one tested here will have the desired robustness and ability for generalization using only the signal of respiratory airflow as input source.

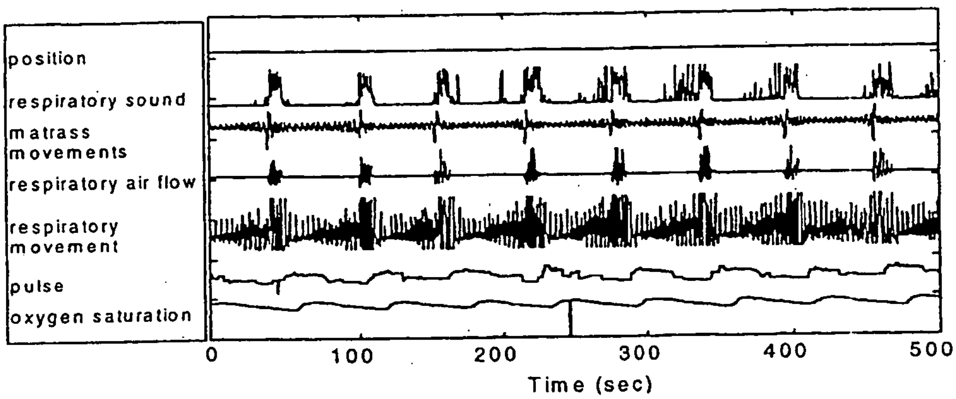


Figure 11. Example of second set of data recordings used for apnea detection.

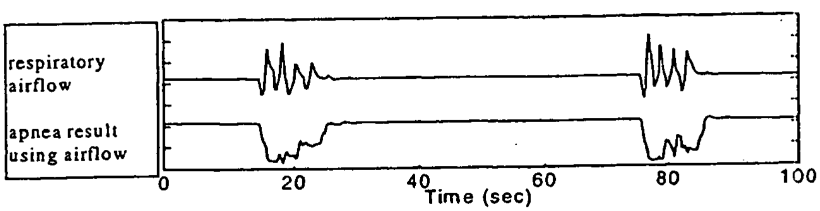
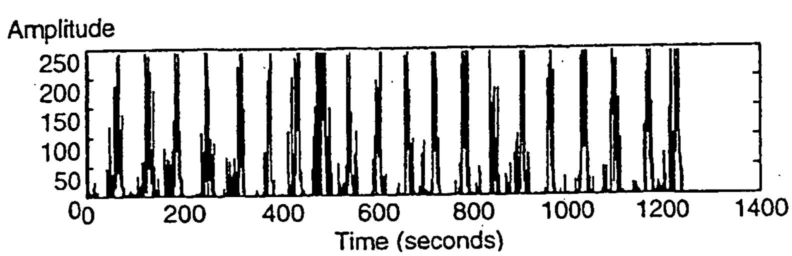


Figure 12. Result of testing a trained neural network using a new data set.

4.4. Detection of apnea using respiratory sound as input to a neural network

The signal of respiratory sound or snoring is very easy to measure and would therefor be convenient for possible apnea detection. The reason for this test is to evaluate the usefulness of sound measurements as input to a neural network with the intention of apnea detection.



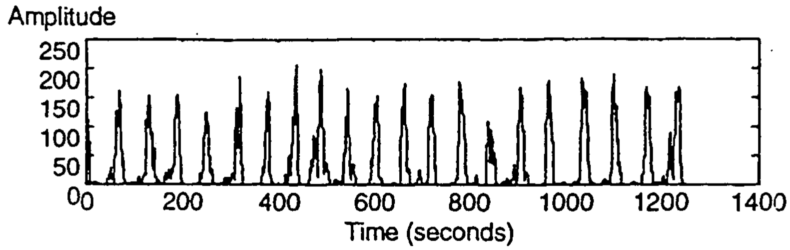


Figure 13. Upper panel show example of respiratory sound signal. The lower panel show 16 points moving average of the upper panel signal.

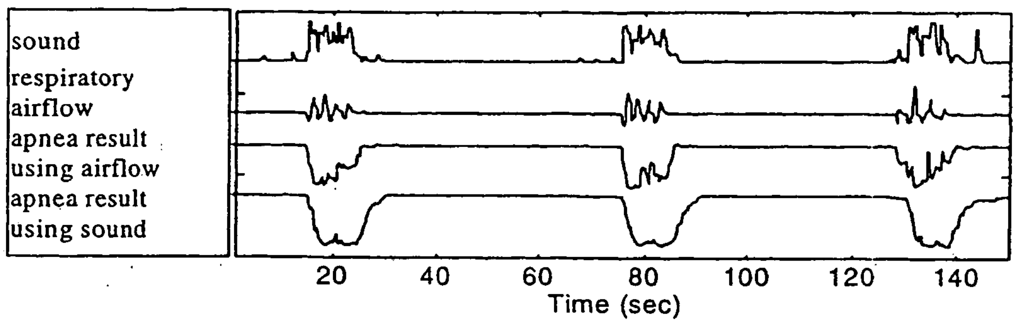


Figure 14. Result of apnea detection using sound respectively respiratory airflow as input to a backpropagation neural network.

The results of figure 14 show that detection of apnea using measurements of respiratory sound is possible. However, the detection of apnea using sound signal seem to have longer time delay compared to using the respiratory airflow signal.

4.5. Respiratory movement

Variable 5 is respiratory movement. This is a way of measuring the abdominal movement of inspiration and expiration during respiration. This is measured using a belt together with a pillow equipped with some compression sensor. The signal is preprocessed by calculating standard deviation of the signal for 16 point moving window. This result in a value of standard deviation for each sampled point in the signal based on the present value together with 15 previous values. The resulting signal can be seen as the second signal in figure 15.

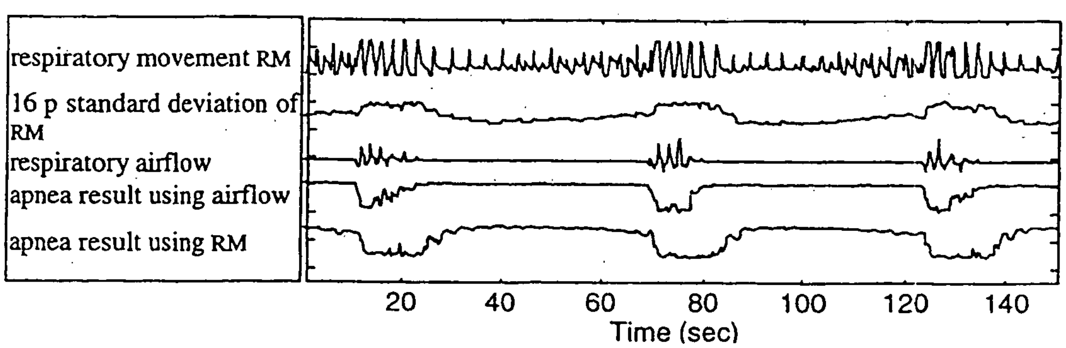


Figure 15. Result of apnea detection using respiratory movement as input to a backpropagation neural network.

Studying the resulting output for the neural net trained using respiratory movement (figure 15) show that this signal is useful for detection of apnea. A more detailed study of figure 16 show that the time delay between beginning of an apnea event and possible detection must be considered high, about 10 second, compared to using respiratory flow as input. The signal is very noisy and some filtering might be useful in this case.

4.6. Using pulse signal as input to the neural network

In this test pulse has been used as the source for input to the neural network training the same way as in 4.4-4.5. In this case the pulse signal is a tendency signal and not an oscillating signal as the earlier cases. This mean that we do not need to do any averaging of the signal, however, the input configuration is the same as in 4.4-4.5.

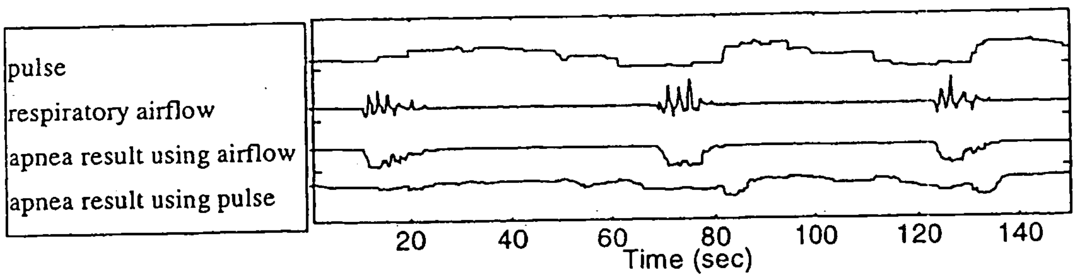


Figure 16. Result of apnea detection using pulse as input to a backpropagation neural network.

Results from training the neural network using pulse as input show that this signal is not suitable as a single parameter for apnea detection. The result from this test do not show any clear detection. This is probably due to the fact that the time delay between apnea occurrence and pulse changes are too long.

4.7. Summary of the neural network tests

Results from testing different configurations of input values to the neural network, presented in sections 4.1- 4.4, show that detection of apnea is possible. The best results have been received using an input configuration consisting of sequences of 10 point averages of the respiratory airflow signal together with the differences between the different averages in the sequence. The conclusion from this is that that early detection is possible, using the respiratory airflow as input. The time delay for this detection is fairly small, about 1-2 seconds. In this case it must be considered that the data used in this study is sampled at a very low sampling frequency, about 4 Hz.

A fair question is then to ask, what is the ability of generalization for the trained neural network. How will the system react if the measured signal is changed in some way, for example change in signal level etc. In order to test this, a new set of data , recorded from a second, different, patient were presented as a test set to the neural network trained using data from the first patient (see section 4.3). The result from this test show that the apnea detection is very well performed, although the test signal from the second patient show different signal levels and a slightly different shape. This result indicates that a neural network based detection/prediction as the one tested here will have the desired robustness and ability for generalization using only the signal of respiratory airflow as input source. Further studies (section 4.5.-4.6) were performed on the available data set in order to investigate the usefulness of other signals as sources of input to a neural network for apnea detection. In these tests artificial neural networks has been trained using the same input configuration as in section 4.3 but constructed from different input signals.

Two of the three different tests using three different input parameters show similar results concerning performance and detectability. However, there are considerable differences in delay time between the beginning of an apnea to the possible detection of this event using the trained neural network. The smallest delay time is gained using respiratory air flow as input 1-2 seconds, this is also the signal that has been used to decide the occurrence of apnea. Using respiratory sound as input result in a delay time of about 5 seconds. The signal of respiratory movement contain a considerably higher degree of noise than the other signals. This will have the effect of increased delay-times of around 8 seconds. The detection results using pulse as input is not very good and do not give any distinct detection.

Although, the results are quite good using respiratory sound or respiratory movement as input, the time delay is considerably higher for these cases compared to using respiratory airflow. As there is a preference for early detection this is an important matter. However, as these signals show a high degree of noise and the sampling rate is very low for the studied signals the performance probably will improve using recordings of higher resolution. Filtering and different methods of pre-processing may also improve performance using these types of signals. Especially the signal of respiratory sound is very interesting for the system for apnea detection, mainly because it is "easy" to measure. Studies have indicated that the frequency information is important for sound recordings of apnea. [17]. This make us believe that there is much to gain from pre-processing of this signal.

The result from this test show that the approach described here has the desired robustness as well as the inherent features needed for a more extended and sophisticated system. It has also been found that early detection of respiratory interruption is possible and that the delay time for this is small. In summary this means that signals from a microphone (placed at the throat), possibly a second microphone, and an air flow sensor will provide the information required to produce a trigger signal..

5. SUMMARY AND DISCUSSION

The present investigation has been carried out in order to see what signals are needed in order to have a redundant input to a control unit for implanted sleep apnea electrodes. At first it would seem reasonable to use an approach in which stimulation is carried out maybe too often, but as long as the patient is not waken up, there is no problem. However, there is the problem of fatigue, i.e. that the stimulation has little or no effect after some time, the hysteresis problem, i.e. if one starts with a low energy stimulation it may be difficult to increase the stimulation. There are also technical problems associated with impedance of the implant electrode, power consumption, etc. Although one would prefer to stimulate the nerve as much as possible (for reason of energy savings), one may need to route the stimulation to a muscle electrode. But the constraint is to stimulate only the appropriate nerve fibers group, while on a large distance the same (hypoglossal) nerve innervates the different muscles which can have opposite effects [6].

Attention has been paid to the pre-processing of these signals and the possibility to use a neural network approach to predict the occurrence of apneas. We feel that the approach described here has the desired robustness as well as the inherent features needed for a more extended and sophisticated system. At this stage we only suggest the monitoring of the air flow and the sound in order to trigger an output to the implanted electrode. A more sophisticated system would include, e.g., the monitoring of the oxygen saturation for long term effects as well feedback information on changes to the electrode impedance. The latter would be used to route the output signal to the electrodes in order to gain maximum efficiency and avoid fatigue problems.

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